The Monitoring Technology for the Latent Risk Population

Alice J. Lin[1], Charles B. Chen[2] and Fuhua (Frank) Cheng [3]

[1]Marshall University, lina@marshall.edu
[2]West Virginia University, cchen6@mix.wvu.edu
[3]University of Kentucky, cheng@cs.uky.edu

ABSTRACT

There are more than 11 million elderly Americans living alone. They belong to a latent risk population that will have emergency situations on a frequent basis. Thus, latent risk populations require constant monitoring. There are many current devices that assist the elderly, but they are not real-time, accessible, or particularly effective. We present a design of novel technology for healthy independent living. The system will contain the devices for fall detection, surrounding environment monitoring, as well as measuring a person's blood pressure, pulse, and oxygen saturation in real time. With this technology, a person's state is not only controlled by that individual; rather, everything is automated so that even if a person falls unconscious, it will still take the necessary steps to call for assistance. The technology we propose is aimed towards both healthy individuals as well as those with disabilities and chronic conditions.

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1 INTRODUCTION

The elderly population (people 65 years or older) numbered 40.4 million in 2010, an increase of 5.4 million or 15.3% since 2000. The number of Americans aged 45-64 who will reach 65 over the next two decades increased by 31% during this decade. Over one in eight Americans is an elderly American. Persons reaching age 65 have an average life expectancy of an additional 18.8 years. The population 65 and over is projected to increase to 55 million in 2020 (a 36% increase for that decade). By 2030, there will be about 72.1 million older persons, over twice their number in 2000 [1].

Falls occur frequently in the elderly population and significantly impair their quality of life. It is estimated that more than one in three elderly individuals living at home fall at least once a year. The risk of falling also rises with increasing age. Falls also lead to decreased mobility, fear of falling, and death [2-4].

Treatment of the injuries and complications associated with falls costs the U.S. over twenty billion dollars annually. Sixty percent of falls occur at home and the danger and severity of falling and the possibility of not having any assistance in case of unconsciousness or extreme injury are primary reasons why many otherwise healthy individuals are forced to leave the comfort and privacy of their own home to live in an assisted-care environment. Furthermore, a fall can have a psychological impact even if the senior is not physically injured. After a fall, many seniors become so afraid of falling again that they limit their activities. This in turn decreases their fitness, mobility and balance and leads to decreased social interactions, reduced satisfaction with life and increased depression. This fear cycle then increases the risk of another fall [5].

2 RELATED WORK

Accelerometers with low-cost and low-power features make a wearable and reliable fall detection system. Multiple sensors with accelerometers placed at various locations in the body are used for real time human movement detection [6-8]. Many systems [2, 9-12] employ triaxial accelerometers to detect fall according to the acceleration of body motion and posture angle. To achieve better accuracy, later systems [13-15] detect fall using accelerometers with barometric pressure sensors, image processors, and gyroscopes.

Information Technology for Assisted Living at Home (ITALH) is a project using new technology to help older citizens live more comfortably [16, 17]. The ITALH includes two items: the IVY project concerns detecting falls at home or in office environments, and the SensorNet project concerns developing an integrated, safe and wireless sensor to monitor the user. However, those previous systems have several restrictions: (1) the methods are device-centric, not user-centric; (2) the devices are expensive and complicated; (3) the information received by the doctor is insufficient to make an accurate diagnose in a timely fashion. In most of the systems, the final decisions are based on the data collected from the sensors and the user cannot express his ideas on his own initiative and just passively accept the decision. In addition, some of the previous systems use acoustic or vibration sensors and image processing software. Most of them are high cost and not universally accessible. Ordinary users cannot control them at their own will. Few systems send an SMS message as a simple alarm. However, the text message is not enough to describe a patient's symptoms, so caregivers cannot have an accurate assessment of the situation.

HOme healthcare sentiNEl sYstem (HONEY) [18] is a home-based fall detection system. It uses a triaxial accelerometer to trigger the detection and deploy speech recognition system and images to reduce the false positive. The trigger depends on the signal vector magnitude (SVM). In that system, if the triaxial accelerometer doesn't detect the fall, the alert will not be sent out. If a person falls slowly, the fall will not be detected.

For the real-time reconstruction of the 3D scenes from video, Narayanan et al. [19] compute depth maps using multi-baseline stereo and merge them to produce viewpoint-based visible surface models. Holes due to occlusion are filled in from nearby depth maps. Koch et al. [20] presented a volumetric approach for fusion as part of an uncalibrated 3D modeling system. Sato et al. [21] proposed a volumetric method based on voting. Each depth estimate votes not only for the most likely surface but also for the presence of free space between the camera and the surface. Werner and Zisserman [22] proposed an approach to reconstruct buildings. It uses sparse points and line correspondences to discover the ground and facade planes. Vaish *et al.* pre*sent* a method which adopts techniques from classical stereo reconstruction, matching corresponding pixels in all images of the light field using essentially robust patch-based block matching [23]. Cornelis et al. [24] presented a system for near real-time city modeling that employs a simple model for the geometry of the world.

3 OUR APPROACHES

Due to the limitations of the above technologies, we design a system that monitors the potential risks to healthy elderly citizens and notifies us of emergency situations in real time. Except for the device for fall detection, by wearing Watching-Over-Me (WOM), a person will be monitored not only in his/her home but also in places where the person spends plenty of time (such as stores, parks, etc.)

The system will contain the devices for fall detection, surrounding environment monitoring, as well as measuring a person's blood pressure, pulse, and oxygen saturation in real time.

3.1 Fall Detection

A triaxial accelerometer is integrated into the fall sensor, and the fall sensor sends early warning information if the trigger conditions are met with handling the three axes' sample values. Many smartphones have the triaxial accelerometer. We can use these smartphones, such as the HTC G3 Hero smartphone, as fall sensors. G3 has a triaxial accelerometer. In addition, the Bluetooth module and a high performance processor on G3 satisfy fall sensor's requirements very well.

It is known and verified that a sensor based on a triaxial accelerometer can distinguish the body movements more precisely when it is fixed on the patient's waist [25]. The triaxial accelerometer will output three acceleration values of x-, y- and z-axis at every sampling point, and the unit is m/s^2. When the body is stationary, the total acceleration of the body is g (the gravity of Earth, 9.8 m/s^2), vertical down. When the body is moving, the acceleration changes along with the movement intensity. Fall sensors are based on the assumption that a fall is usually associated with a magnitude impact. An estimation of the degree of body movement intensity can be obtained from the signal vector magnitude (SVM). Define SVM by the relation:

$$SVM = \sqrt{x_i^{\,2} + y_i^{\,2} + z_i^{\,2}}$$

where x_i is the i-th sample value of the x-axis signal (similarly for y_i and z_i). Therefore, comparing the SVM to a preset SVM threshold (SVM_th) allows detecting the associated fall. Similarly, when the body falls, the space relationship between body and ground also changes significantly. In order to determine the space posture of the body, Tilt Angle (TA) is defined as the angle between positive z-axis and SVM by the relation:

$$TA = \arccos(z/SVM)$$

where z is the sample value of z-axis signal. TA refers to the relative tilt of the body in space.

We also need an angle distinction between the upright postures of sitting and standing, as well as the lying in various conditions. Karantonis's works [8] provide the range of TA corresponding to the different body postures: if the patient's TA is from 0 to 20°, it is classified as standing, and values from 20 to 60° indicates a sitting posture; if TA is between 60 and 120°, it is regarded as a lying posture. In most cases, a fall starts from a standing posture, and directly ends with lying on the floor. However, no fall would be predicted if the user falls in such a way that he or she was not parallel with the ground. This is important in various cases during a fall. A user will try to grasp a wall, chair, or other objects and end up slumping next to the object, such as sitting on a chair, rather than lying on the floor. Therefore, a sitting posture following a magnitude SVM is regarded as a fall.

3.2 Surrounding Environment Monitoring

Part 1: WOM (see Figure 1), portable signaling devices, are on the elder person's side at all times. There are two sets of sensors are complementary. One set of biochemical sensors detect biochemical markers in the elder person, such as blood glucose, blood pressure, pulse, oxygen saturation, sweat pH and salt balance. Biochemical abnormalities occur when the elder person's biochemical and physiological parameters exceed the threshold and reach a dangerous level. Another set of sensors are image sensors – tiny cameras, which are mounted on the elder person's clothes or in a hat. With today's camera hardware it has become possible to capture real-time images of the surroundings.

There has been a considerable amount of work involving 3D reconstruction from aerial images [26, 27]. The system collects video streams, and automatic, real-time 3D reconstruction from video of scenes. The core algorithms operate on the frames of a single video-camera as it moves in space. The reconstructions are based on frames captured at different time instances by the same camera under the assumption that the scenes remain static [28]. Compared to laser scanning, an attractive property of passive, image-based stereo techniques has their ability to create a 3D representation solely from photographs and to easily capture the scene from different viewing positions to alleviate occlusion issues [29]. Our system continually learns from environmental data, and then constructs the 3D scene. The 3D scene is cumulated as the person passes through more and more places. This information is stored as standard scenes. Each time the person appears in the same scene the system compare the surrounding environmental information with standard scenes information.

3.3 The Processing Unit

Part 2: The processing unit. Figure 1 is the framework of the system. First, the system acquires real-time data from the surrounding environment and the health data from the person wearing WOM. The devices periodically compare the real time data with the learned data. When an abnormal event occurs, it will make a decision and inform the pre-determined parties (ambulance, caregiver, family members, etc.).

The system will be based on its experience to detect progressive decline in physical and cognitive abilities by determining the abnormal scene. To achieve this, the system compares recent input data of the scene with the data of the routine scene. For example, suppose a person falls down or is staggering, the system integrates the data with health data to make the decision if the person is in critical condition. If the system detects this kind of situation it automatically calls 911. It also triggers an alert system in the WOM. If there are people around, they will also be alerted.

3.4 Monitoring System

In the part 3, the system transfers the data to a real-time 3D scene and 3D character. The data is continuously fed and the character and surrounding environment are updated all the time. The person's activities can be viewed on mobile devices. The person wearing the WOM can control who can see his or her activities.

4 CONCLUSION

We have presented a design of novel technology for healthy independent living. The advantage of our technology is that we are able to detect the person's dynamic state. Our method is based on surrounding environmental information, and fall detection and health data as auxiliary information. As long as the person is wearing the WOM, it is all automated. Even if the person suddenly falls unconscious, it will still take the appropriate actions. Thus, this technology has multiple benefits and can be targeted to both disabled and healthy individuals alike.

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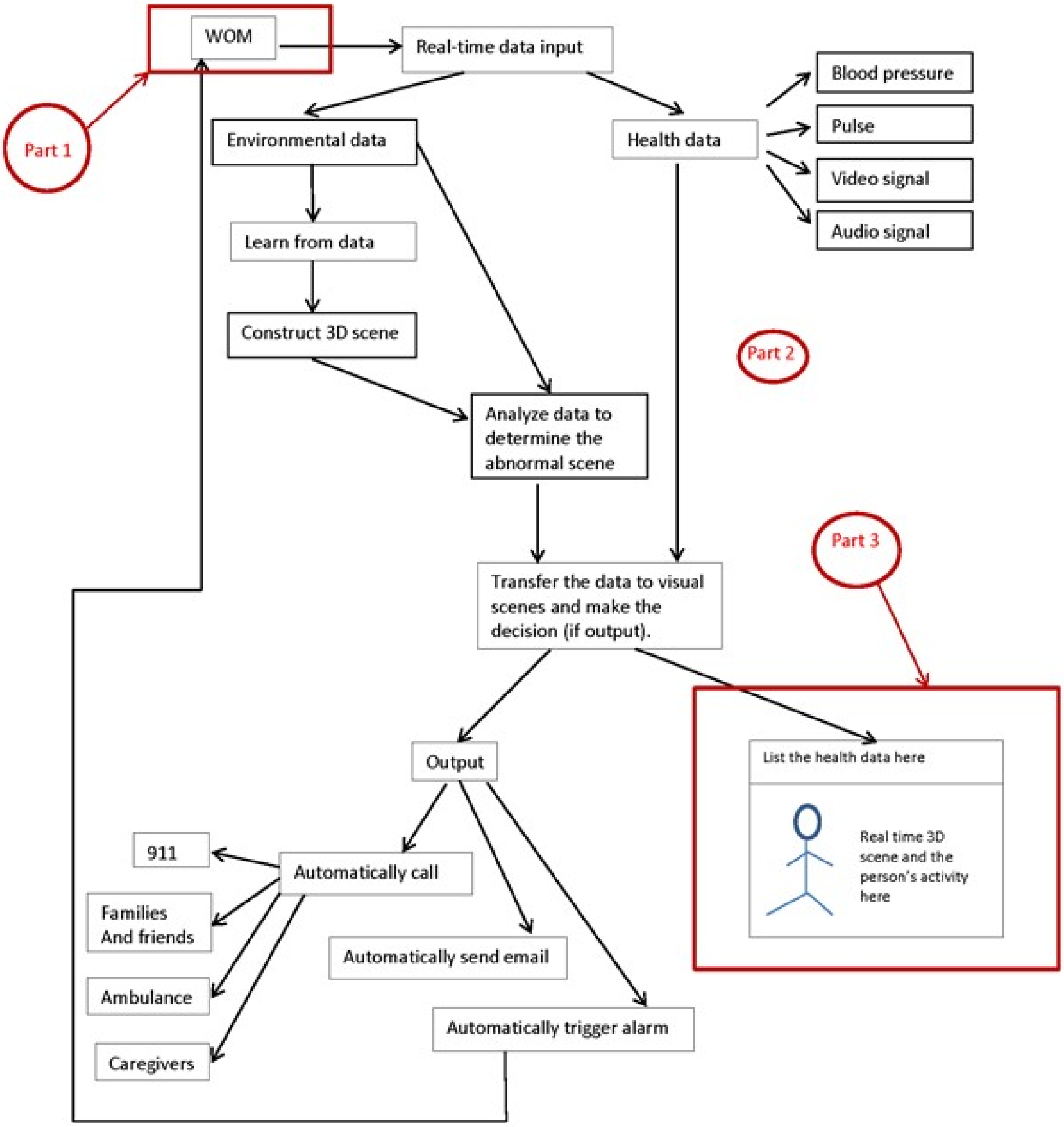

Figure 1: The framework of the system